Gait Recognition Using WiFi Signals

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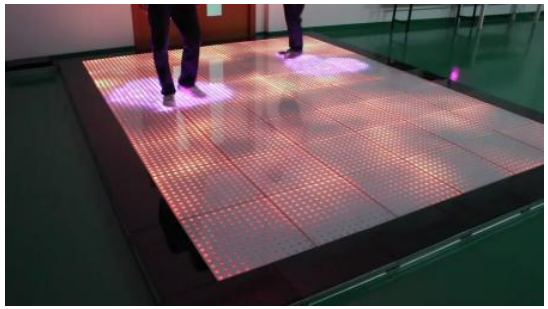
Gait Based Human Authentication & Identification

- Human Authentication
  - Problem Statement: Are you Trump or not?
  - Why need gait based human authentication?
    - Multi-factor human authentication

- Human Identification
  - Problem Statement: Which one of the following people are you: Trump or Hillary?
  - Why need gait based human identification?
    - Customization

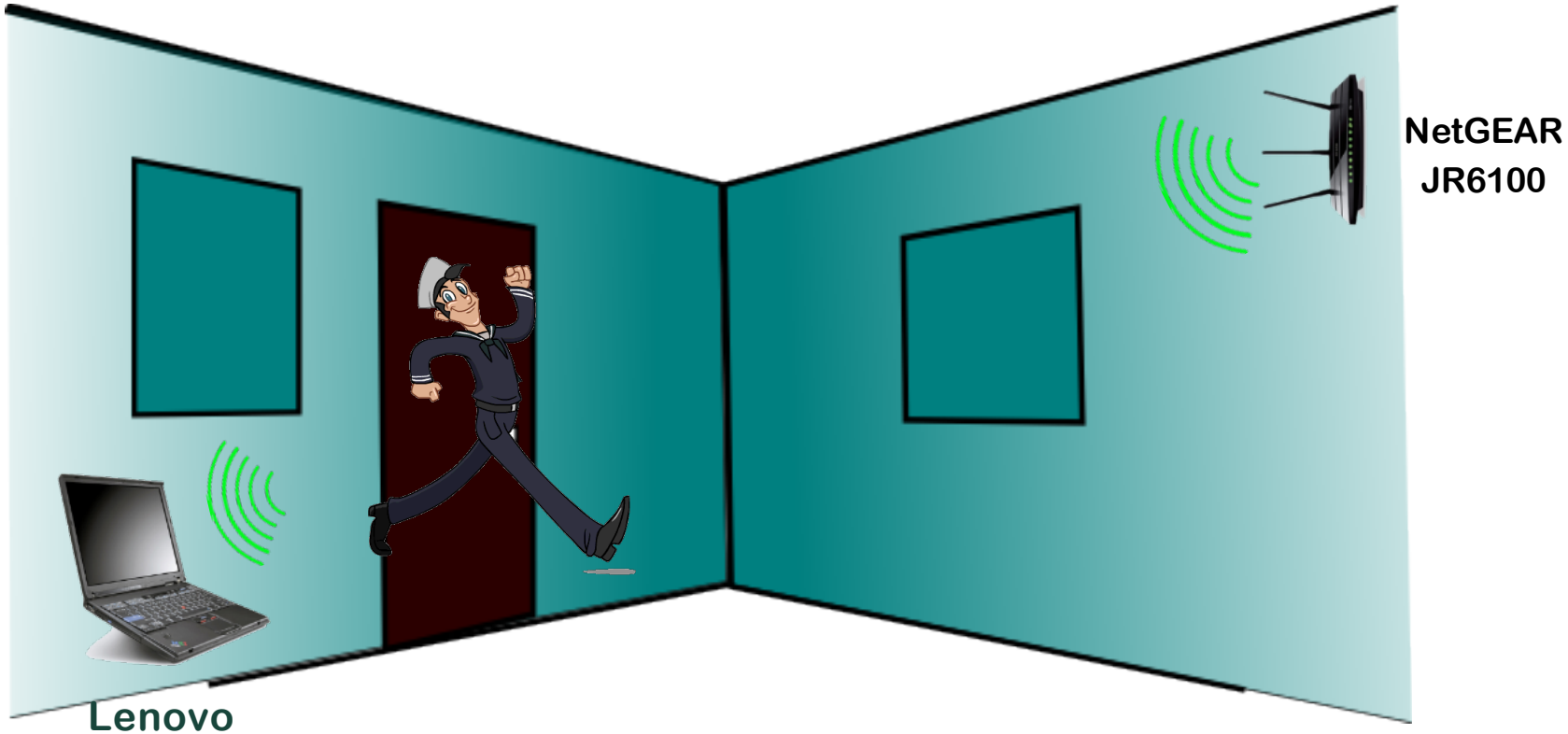
Gait Based Human Authentication & Identification

- **Why possible?**
  - Individually unique gait patterns
- **What have been done?**
  - Video camera
    - Cannot work in dark
    - Privacy concern
  - Wearble sensors
    - Inconvenient
  - Floor sensors
    - Expensive
- **What do we propose?**
  - WiFi signals



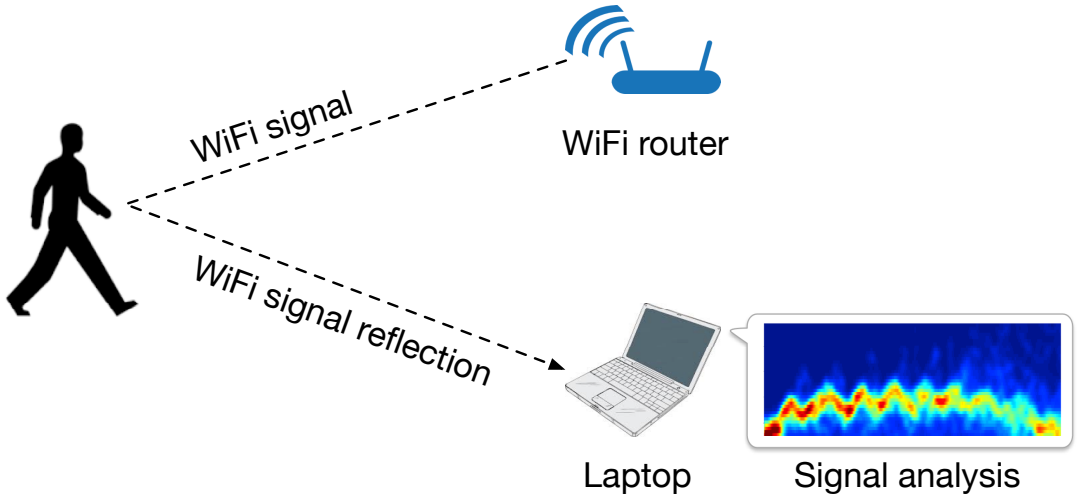
WiFiU: Gait Based Human Authentication & Recognition Using WiFi Signals

- Using commercial off the shelf devices
- Woks in dark
- Privacy friendly



Key Insight

- Human body reflects wireless signals

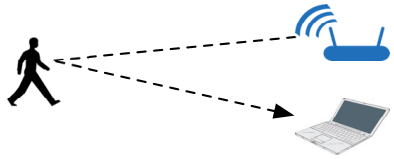


- Chanel State Information (CSI) has huge amount of useful information about environmental changes
  - 2,500 samples per second
  - Complex valued samples with 8 bit accuracy
  - On 30 subcarriers for each antenna pair
- So, commercial WiFi devices can act as Doppler Radars to measure human activities

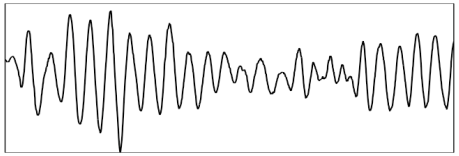
System Architecture

Data collection and pre-processing

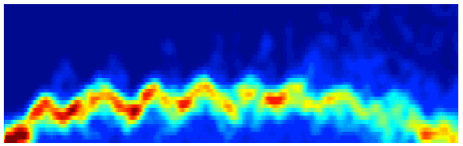
1. CSI data collection



2. PCA denoising

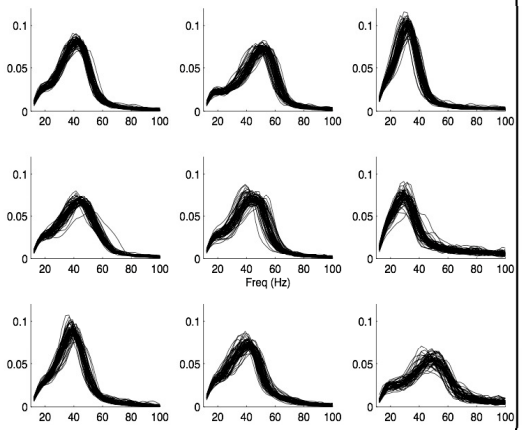


3. Spectrogram generation



Feature extraction

- Gait cycle time
- Torso speed
- Footstep size
- Leg speed
- Spectrogram signature



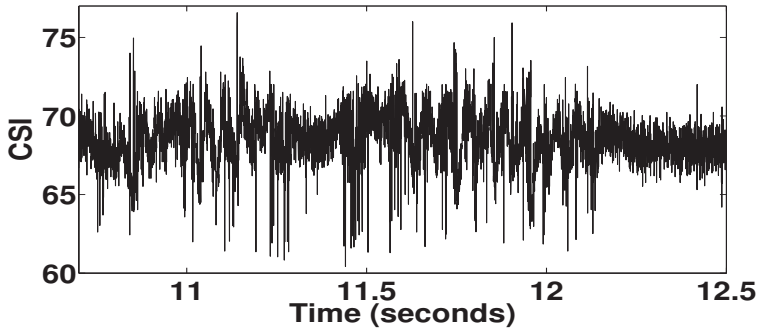
Identification

1. Model generation
   Training data collection

2. Prediction
   SVM based prediction

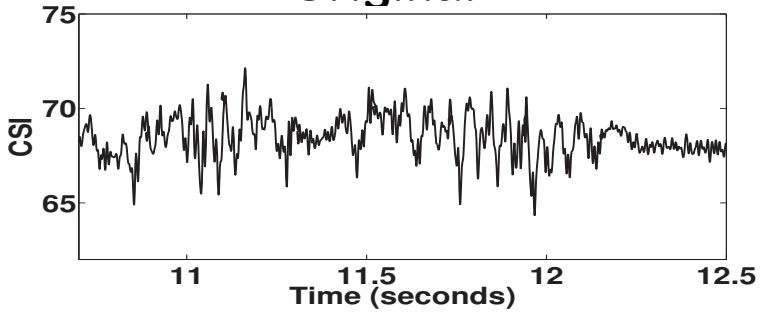
How to deal with noisy signals?

- Signals from commercial WiFi devices are very noisy



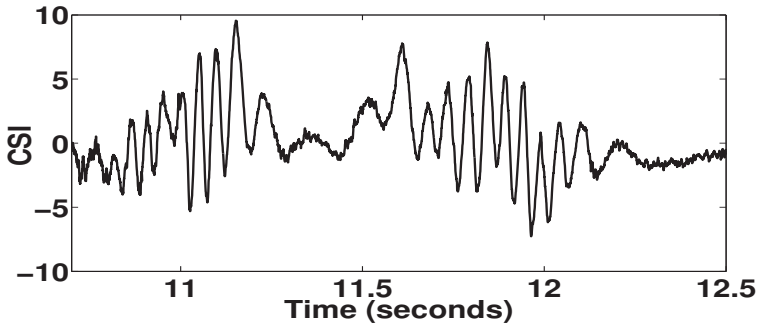
Original

- Traditional filter based denoising approaches not work



Low-pass filter

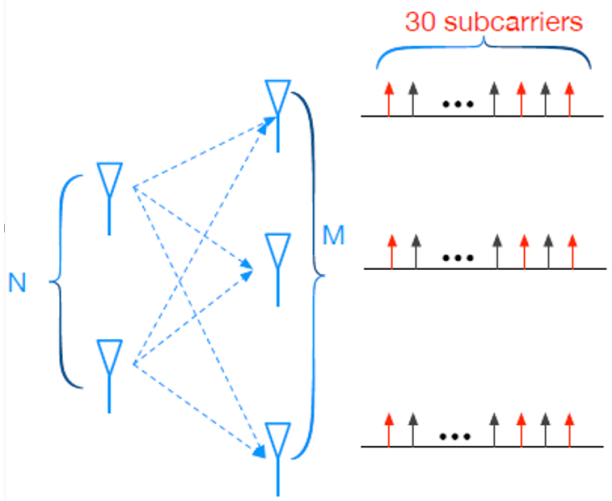
- We proposed a Principal Component Analysis based approach in our MobiCom 15 paper

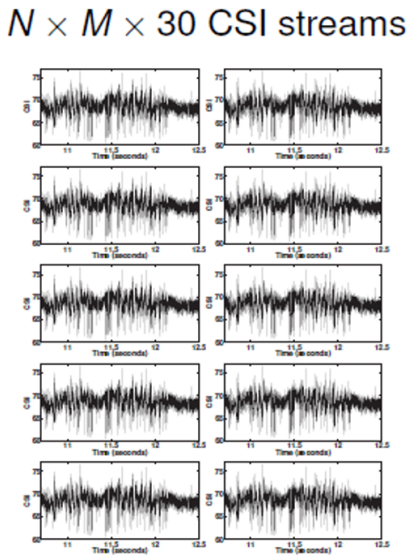


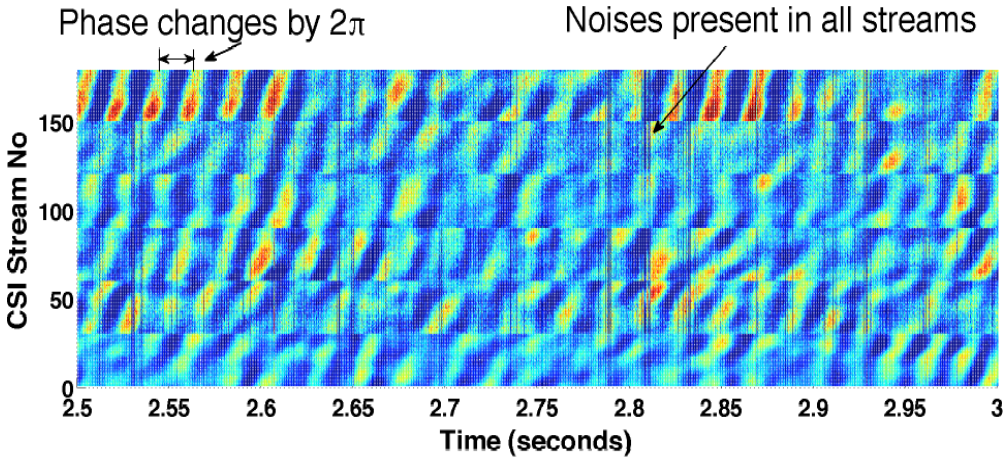
PCA

PCA Based Noise Reduction

- Changes in CSI streams caused by human movement are correlated
  - Theoretically proved
  - Experimentally validated





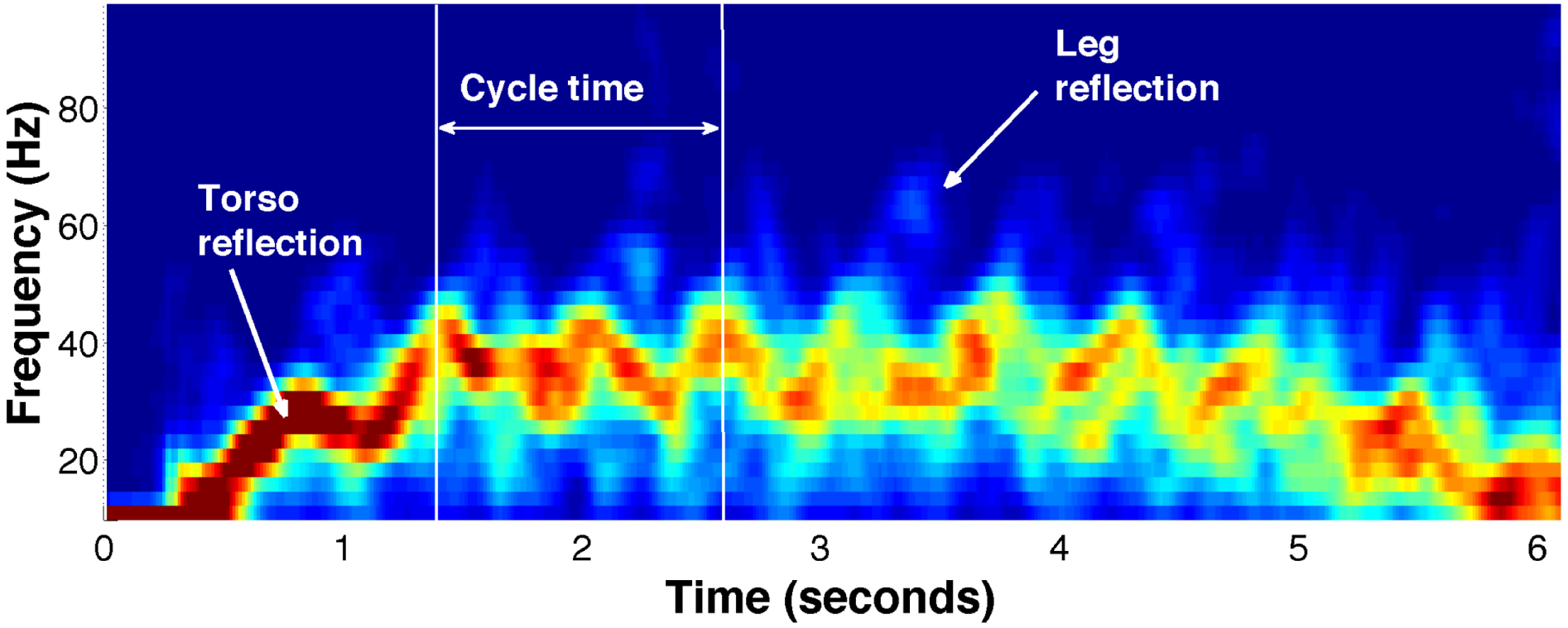


How to extract gait information?

- Challenge: signal reflections of different body parts are mixed together in the wave form.
- Insight: different body parts move at different speeds
  - Signal reflections of different parts have different frequencies.
  - CSI fluctuations of different frequencies are separable in the frequency domain.
- How: convert waveforms into time-frequency domain
  - Use Short-Time Fourier Transform (STFT) to convert each slice of waveforms to a spectrogram.
  - Spectrogram 3 dimensions: time, frequency, and FFT amplitude
  - Window size: tradeoff between frequency and time resolutions
    - Larger: higher frequency resolution, low time resolution
    - Smaller: low frequency solution, high time resolution
  - Our choice: FFT size=1024 samples, window size=32 samples
    - Frequency resolution=2.44Hz, time resolution=12.8ms

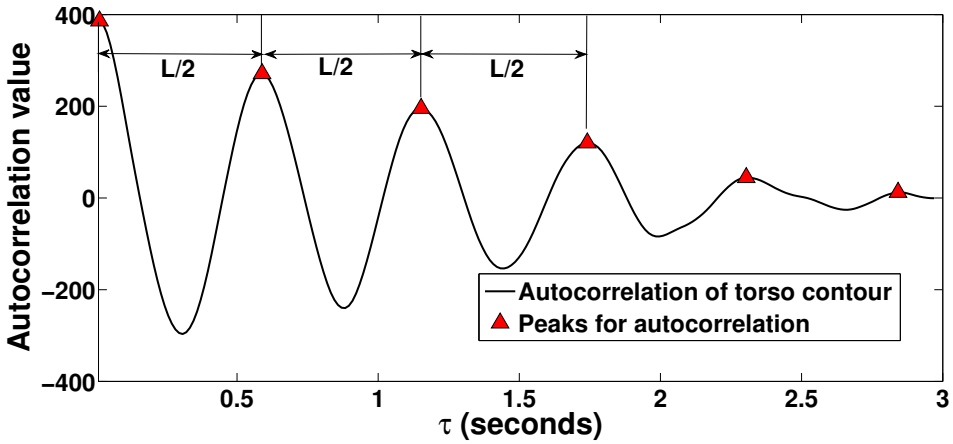
Spectrogram Enhancement

- We apply spectrogram enhancement techniques to further reduce noise.
- Insight: CSI spectrograms give similar information as the expensive Doppler radars

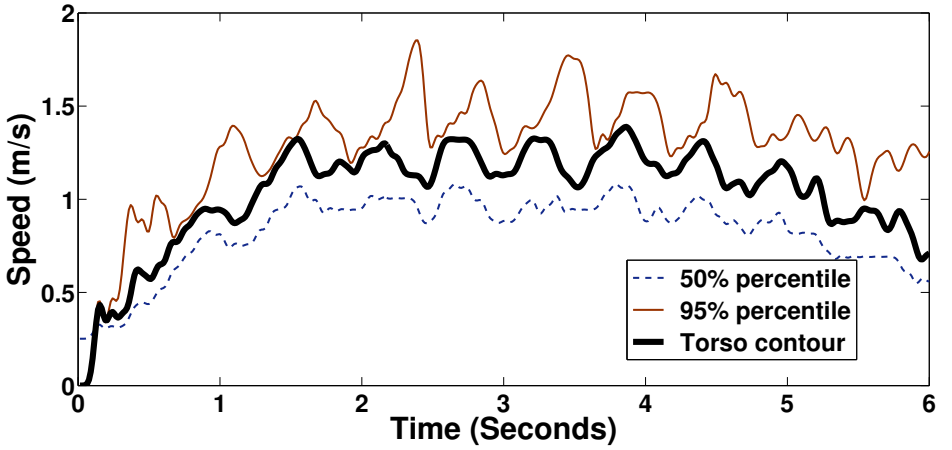


Feature Extraction

- Gait cycle time
  - Obtain upper contour of the torso reflection.
  - Use autocorrelation of upper contours to estimate gait cycle time.

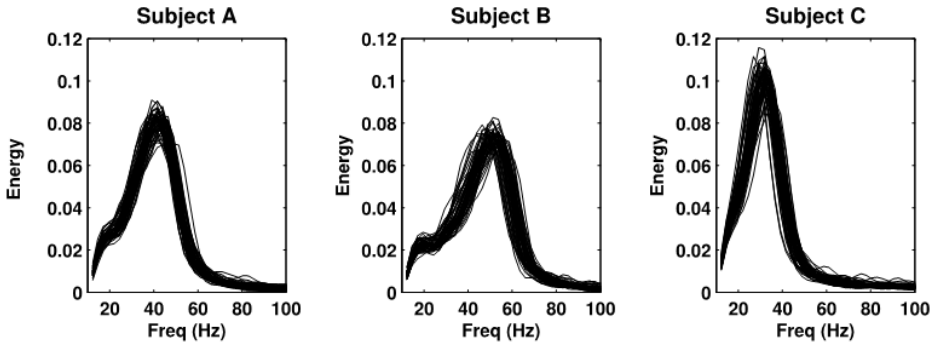


- Torso and leg speeds
  - Use percentile method for Doppler radars



Feature Extraction

- Spectrogram signatures
  - Motivation: gait cycle time and torso speeds are not enough
  - Idea: use the distribution of reflected energy on predetermined frequency points as signatures
  - Why: energy distributions give an overview on how different body parts move at a given stage of walking
- Extraction method:
  - Divide each walking cycle into 2 phases by torso contour curve.
  - Further divide each half-gait-cycle into 2 stages of leg swinging.
  - For each stage, calculate the normalized energy on 40 frequency points.



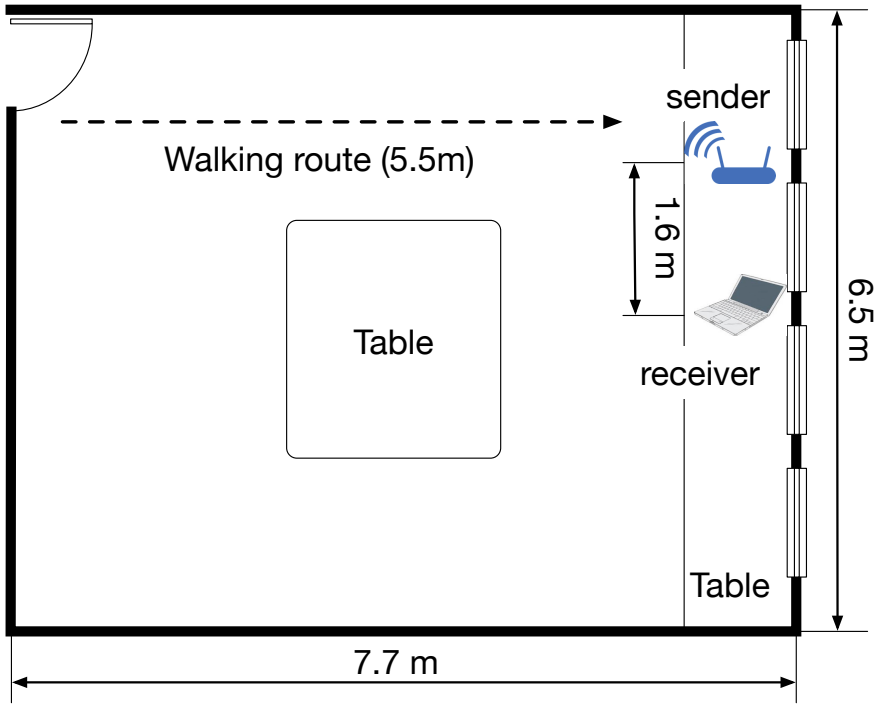
Training and Identification

- Use SVM to generate model
  - Feature vector size = 170
  - Sample size = 40

- Two applications
  - Single user authentication
  - Multiple users identification

Data Collection

- Devices
  - NetGear WiFi Router
  - ThinkPad Laptop
    (with Intel 5300 nic)
- Dataset
  - 50 users
  - 50 walking samples for each user
  - Walking for 5.5 meters
- Metrics
  - Distance
  - Effectiveness
  - Robustness
  - Efficiency



Distance

- WiFiU can detect a walking human subject at a range as long as 14 meters with an accuracy of 92%.

Accuracy

- Human authentication
  - Average FAR=8.05%
  - Average FRR=9.54%

- Human identification
  - Top-1 accuracy=92.31%
  - Top-2 accuracy=97.58%
  - Top-3 accuracy=98.86%

Robustness

- Evolution of human gait does not significantly affect WiFiU accuracy
  - Collected data over 4 months

- WiFiU is also robust to small changes in environments such as chair movements.

Efficiency

- WiFiU can run in real time on laptops and desktops.
  - Less than 1 second.

Limitations

- Single person walking
  - Multiple users are OK as long as other remain roughly static.
- Predefined walking path
  - Doppler spectrograms are sensitive to walking directions.
- Limited accuracy
  - Not enough for single-factor authentication.

Conclusions

- We demonstrate the feasibility of using WiFi signals from COTS devices for gait based human authentication and identification.
- We propose signal processing techniques for converting raw noisy WiFi signals to high-fidelity spectrograms.
- We propose methods to further convert spectrograms to gait features.

thank you!